World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

Check for updates

AI for carbon emissions monitoring: Computer vision and remote sensing for automated carbon emissions tracking

Sai Santhosh Polagani *

Product Manager AI, Salesforce, Charlotte, United States.

World Journal of Advanced Research and Reviews, 2025, 26(02), 2324-2334

Publication history: Received on 04 April 2025; revised on 10 May 2025; accepted on 12 May 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.26.2.1847

Abstract

The exact measurement and scale-up of carbon emissions are essential to fulfill environmental targets and satisfy regulatory standards. The study investigates how AI-powered computer vision and satellite-based remote sensing technologies track industrial sectors' carbon emissions in an automatic and near-real-time manner. The proposed system merges CNNS with spectral analysis and geo-temporal data fusion mechanisms to identify and measure emissions from power plants, manufacturing facilities, and transport centers. The system uses satellite imagery (for example, Sentinel-5p and Landsat) and environmental sensor data to enhance measurement accuracy and spatial resolution. The confidence-weighted emissions estimation model incorporates features to decrease incorrect emissions detection while delivering auditable information streams to ESG auditors and governments. The developed system advances AI-based environmental monitoring technologies while enabling transparent verification and economic analysis, which allows global enforcement of decarbonization strategies.

Keywords: Carbon Emissions Monitoring; Satellite Remote Sensing; Artificial Intelligence (AI); Computer Vision; Environmental Data Fusion

1. Introduction

Global warming mitigation efforts have increased due to the rising effects of climate change over the last few decades. The main objective of this initiative includes climate targets set at below 2°C from pre-industrial times, as stated in the Paris Agreement, while requiring substantial cuts in carbon output. These targets will become a reality by combining primary energy and industrial transformation with strong emissions tracking systems that operate with total transparency. Identifying and verifying carbon emissions is essential for monitoring international accords and supporting government decisions, thus directing sustainable technology funding. The existing monitoring of emissions confronts various obstacles because measurement systems require better scalability, and data collection must improve its accuracy across all geographic areas and industrial areas.

Traditional monitoring practice scaling faces major obstacles because it relies on sensors that operate at the ground level and requires manual data collection processes. The current approaches deliver beneficial localized information, but their restricted coverage and limited information frequency create possibilities for incorrect results. Generating trustworthy and thorough emissions inventories becomes difficult because emissions sources show variability between extensive fixed facilities and dispersed mobile and scattered sources. Timely interventions face impairment because data collection follows analysis in numerous situations. The growing industries with intensified regulatory requirements require powerful monitoring technologies characterized by maximum efficiency and precise performance at large scales.

* Corresponding author: Sai Santhosh Polagani

The study provides a new monitoring system that employs AI-powered computer vision and satellite remote sensing for automatic carbon emissions tracking. The proposed system integrates high-resolution satellite imagery with cutting-edge convolutional neural networks and spectral analysis for superior monitoring results beyond standard procedures. The technological partnership delivers real-time emission data collection abilities across enormous geographical domains, generating a thorough moving picture of carbon emissions. Multiple data source integration capabilities in the system create more precise detection outcomes and enable the production of trackable data flows necessary for regulatory requirements. Business-centric technology can effectively back environmental enforcement systems and decarbonization plans because it provides reliable data while being flexible to industrial and environmental speed.

2. Literature Review

2.1. Current state of carbon emissions monitoring

The vital role of carbon emissions monitoring emerged during recent decades to determine the effects of climate change alongside their management strategies. The emissions tracking predominantly depended on conventional human inspection methods and stationary ground sensors. Field technicians perform inspections through manual checks, which involve scheduled on-site visual evaluations that require a lot of time and show human interpretive limitations. Location constraints and low data precision at fixed points restrict the continuous data acquisition through ground sensor networks. The current regulatory compliance systems keep functioning with their established inspection programs, yet lack the precision and expansion capabilities needed for contemporary environmental problem solutions. Environmental change detection faces obstacles due to the existing methods that struggle with geographical restrictions, expensive operations, and slow information processing speeds, which delay rapid decision-making.

Table 1 Comparison between traditional and modern carbon emissions monitoring methods

Aspect	**Traditional Methods**	**Modern Automated Approaches**
Data Collection	Manual inspections, fixed sensor networks	Satellite imagery, automated computer vision, and sensor fusion
Scalability	Limited, often geographically constrained	High, enabling global monitoring via remote sensing
Temporal Resolution	Periodic and delayed data availability	Near real-time monitoring and data streaming
Operational Cost	High, due to labor intensity and maintenance	Reduced, thanks to automation and remote operations
Accuracy	Affected by human error and environmental variability	Enhanced by multi-modal data fusion and advanced machine learning

2.2. Advancements in Related Technologies

The environment monitoring sector underwent a substantial change because of contemporary technological developments. Computer vision represents a modern, transformative instrument scientists use in environmental monitoring. Deep learning algorithms, especially convolutional neural networks (CNNS), enable computer vision systems to scan large image datasets for detecting minimal visual patterns that signify emission activities. Automated systems perform better by identifying unrecognizable instances while classifying emission points and measuring quantities beyond human capabilities.Modern remote sensing technologies and satellite imagery have experienced simultaneous advancement. Sentinel-5p and Landsat platforms now deliver extraordinary satellite data combinations that enable air pollution observation throughout extensive regions. These satellites can capture current images, which prove essential for monitoring short-term emission occurrences and detecting changes in pollutant concentration levels. Observational data obtained from space satellites creates more comprehensive coverage while improving measurement precision because it validates data points collected from multiple data collection methods.

2.3. Gap Analysis

The modern environmental field has undergone drastic changes because of recent technological developments. Computer vision is a technology that has transformed environmental applications into new possibilities. Deep learning algorithms, especially convolutional neural networks (CNNS), enable computer vision systems to scan large image datasets for detecting minimal visual patterns that signify emission activities. This technology executes accurate detection of oddities while establishing emission source divisions and measuringunreachable product quantities through traditional inspection methods.Modern developments in satellite imagery and remote sensing have been parallel. Sentinel-5p and Landsat platforms offer new possibilities to obtain detailed multi-dimensional satellite data, enablingmonitoring of large atmospheric pollutant distributions. The satellites acquire immediate visual data to help researchers locate fast emission releases while showing how pollutants evolve. Data collected through satellites adds better spatial information to ground-based sensor readings, thus leading to more precise emissions measurements because measurements verify each other across different systems.

3. Proposed Multi-Modal System Overview

This integrated framework uses current artificial intelligence (AI), computer vision, and remote sensing technologies to function as a multi-modal system. The system maintains an architecture enabling automatic carbon emission identification, quantitative analysis, and ongoing emissions tracking throughout industrial areas. The system integrates multiple independent yet compatible technological aspects using a centralized data fusion facility at its top logical level. The design combines components that enable quick environmental data processing and flexible capacity to monitor static facilities and moving urban areas.

3.1. System Architecture

The system's architecture presents data acquisition, processing, and decision-making in sequential order. The first stage of data collection consists of receiving data from various sources, including high-resolution satellite imagery coupled with on-ground sensor networks. The pre-processing unit receives data from multiple sources that undergo spatial-temporal standardization, creating an organized set for advanced analysis. Subsequent processing involves the combination of AI algorithms that include CNNS and spectral analysis methods with geotemporal fusion operations. The system operates optimally through this junction, allowing precise measurement of carbon emissions detection and quantification. The decision layer merges output data into practical information,enabling live tracking and meeting regulatory requirements.

3.2. Three-tier architecture for distributed systems

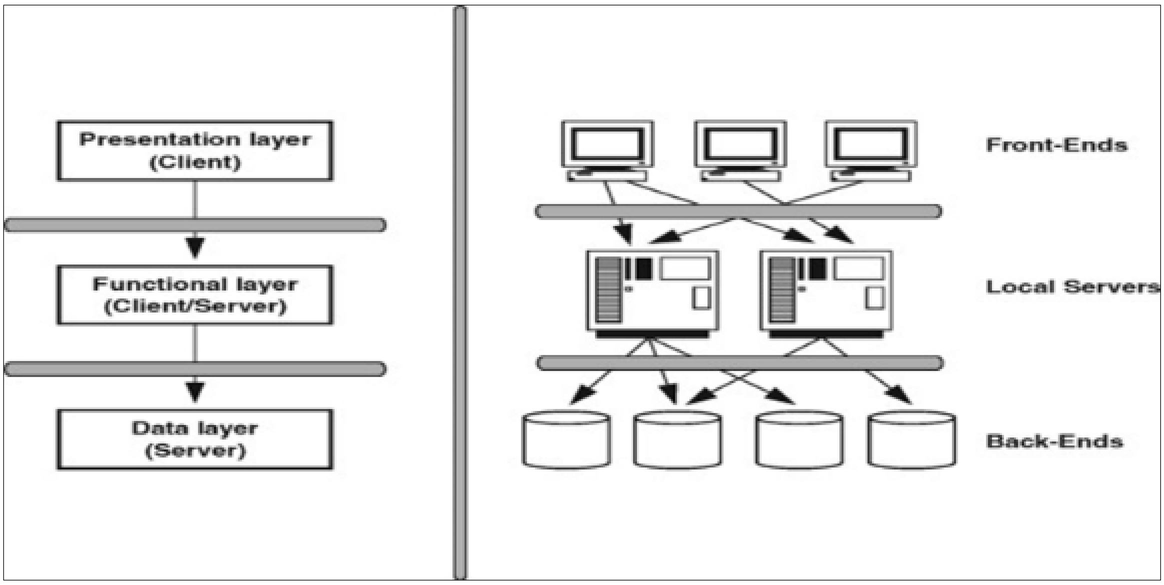

Figure 1 Conceptual diagram of the multi-modal system architecture

The layers of three-tier architecture are often implemented as independent processes that run on separate computers. The presentation layer assumes the role of a client, the functional layer assumes the role of a server for the user interface and the role of a client for data objects, and the data layer acts as a server. This allows us to describe configurations for front-end PCS, local application servers, and centralized back-end machines. Figure 9.5 shows an example of a three-tier architecture.

3.3. Key Components

3.3.1. Convolutional Neural Networks (CNNS)

The basic operational unit for extracting image features within the system relies on the CNN network architecture. The sophistication of CNNS enables them to identify emission signatures that represent carbon output by processing high-dimensional visual data from satellite imagery and aerial photographs. Multiple layers in CNNS refine raw inputs till they become meaningful patterns through the sequence of convolutional and pooling layers and fully connected layers. Trained using detailed emission data with different profiles, the models develop skills to catch actual emissions from environmental noise in the background. Reliability of the monitoring methodology depends on this essential feature, which prevents wrong positive results.

3.3.2. Spectral Analysis

The detection and measurement of particular gases by spectral analysis occur by identifying unique spectral signatures. The distinct wavelengths designate absorption and emission points of electromagnetic radiation for various gas types. The system detects these signatures precisely through multi-spectral imagery analysis, emphasizing Hyperspectral and multispectral bands. The absorption spectra of gases, including CO_2 and CH_4, can be detected in the shortwave infrared (SWIR) and thermal infrared (TIR) frequency regions. The detection system performs better in difficult atmospheric conditions because of this method. Hyperspectral imaging and multi-spectral filtering enable the system to find carbon emissions among background noise and provide precise measurement data for atmospheric gas concentration analysis.

3.3.3. Geo-Temporal Data Fusion

Geo-temporal data fusion performs information integration involving space-time dimensions to enhance tracking, quantify emissions, and forecast their future distribution. The algorithm connects dynamic satellite data (daily satellite passes) with continuous air quality monitoring stations with static ground-based sensor data. Time-series analysis enables the detection of emission trends and sudden abnormalities, while spatial analysis provides exact locations of all emission points. The system reaches real-time resistance because it summarizes data from various sources through its fusion process. This system allows operators to identify brief emission accidents at specific industrial facilities and longer-term emission trends across seasons to create better environmental policies through advanced enforcement opportunities.

Table 2 Summary of key components and their roles

Component	Role	Key Techniques/Features
Convolutional Neural Networks (CNNS)	Processes satellite imagery; identifies visual emission signatures.	Convolutional filters, pooling, and feature extraction.
Spectral Analysis	Detects chemical-specific spectral signatures to isolate emissions.	Hyperspectral imaging, multi-spectral filtering.
Geo-Temporal Data Fusion	Combines spatial and temporal data to improve tracking accuracy and resolution.	Time-series analysis, spatial mapping, and data integration.

3.4. Integration of the Data Sources

The principal value of this proposed system emerges from its creative combination of several data source inputs. The satellite data acquired from Sentinel-5p and Landsat platforms enables extensive spatial monitoring and frequent observations covering all remote and inaccessible regions. The system obtains enhanced reliability in its emission estimation through dual-layer validation. Combining satellite and on-ground sensor network data makes presenting localized high-frequency environmental data possible. The system's central data fusion mechanism harmonizes dissimilar formats, resolutions,and timing inconsistencies between data sources. An algorithm-based module aims to match satellite observation data with present-time ground-based data measurements, becoming less prone to delays and environmental changes. The combined system enhances the accuracy of emission tracking performance while allowing it to function across multiple industrial scenarios. The dual-source validation system enhances its integrity by creating dependable and auditable data streams that serve regulatory needs and environmental governance requirements.

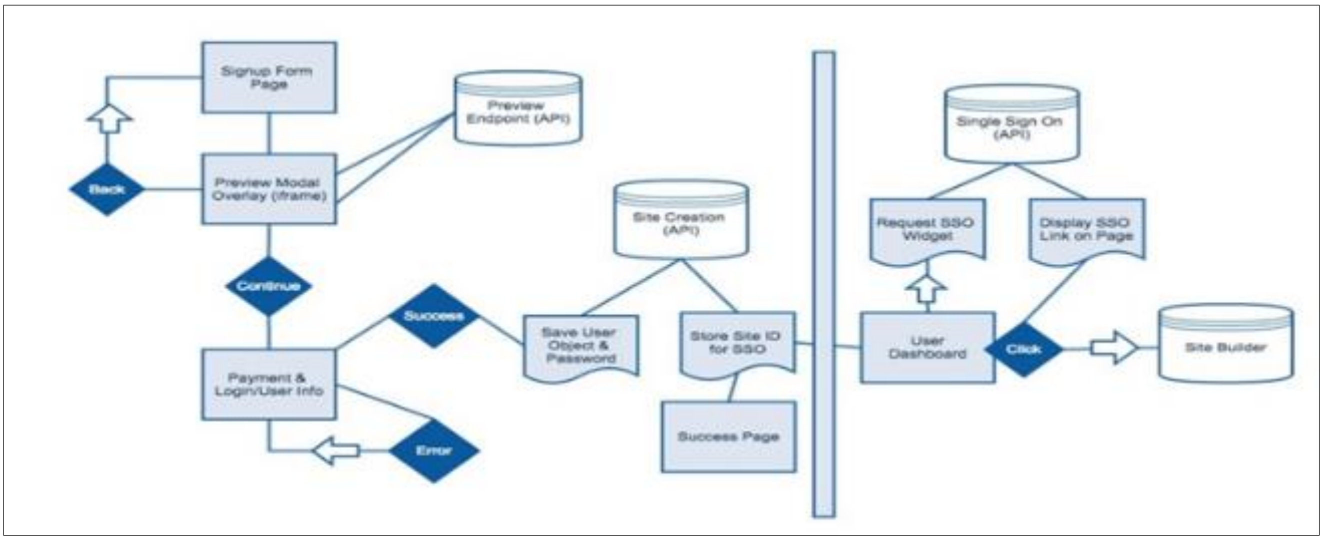

Figure 2 Data Integration Workflow

4. Methodology and technical implementation

According to this segment, the proposed AI-driven carbon emissions monitoring system will depend on the following technical components. The research explains how the data sources were utilized alongside the analytical methods for detecting and measuring emissions, while showing how the emission prediction model was structured. The system combines multi-source data with advanced machine learning algorithms to create a reliable, sustainable solution for immediate environmental surveillance.

4.1. Data acquisition

4.1.1. Satellite Imagery Sources

The satellite imagery infrastructure of the monitoring system functions with high-resolution multispectral imagery. Two fundamental satellite data sources include Sentinel-5p and Landsat. The European Space Agency (ESA) operates Sentinel-5p, which utilizes the Tropospheric Monitoring Instrument (TROPOMI) to track nitrogen dioxide (NO_2), carbon monoxide (CO), and methane (CH_4) pollutants with daily global coverage. The instrument provides the necessary resolution and high revisit frequency to monitor and analyze large emission patterns.The USGS and NASA together operate Landsat satellites that deliver medium-resolution optical and infrared picture data. Landsat imagery provides complementary high-resolution visual data of ground features through its non-atmospheric purpose, helping Sentinel-5p's team locate industrial emission sources accurately.

4.1.2. Integration of Ground-Based Environmental Sensors

A system enhancement method to improve the accuracy of satellite-based estimates includes integrating information sourced from ground-based environmental sensors, such as air quality monitors, weather stations, and industrial emission detectors. The sensors provide detailed real-time measurements for CO_2, SO_2, and PM2.5 pollutants used to verify satellite-collected data. AI models receive ground data for model training, validation, and evaluation purposes.

Table 3 Characteristics of data sources used in the emissions monitoring system

Data Source	Spatial Resolution	Temporal Resolution	Pollutants Tracked	Role in System
Sentinel-5P	~7 km × 3.5 km	Daily	NO_2, CO, CH_4, SO_2	Atmospheric gas detection
Landsat-8/9	15–30 m	16-day cycle	Visual/thermal imagery	Source localization
Ground Sensors	Point-based	Real-time to hourly	CO_2, SO_2, PM2.5	Calibration and validation

4.2. Analytical techniques

4.2.1. Convolutional Neural Networks (CNNS) for Emissions Detection

CNNs function as a tool for emission-related feature detection and segmentation within satellite images. Training these models proceeds using datasets where emission plumes, industrial facilities, and atmospheric anomalies receive manual annotation markings. Spatial pollution event patterns, including shape characteristics, colour patterns, and textural outlines, become recognizable to CNNS. At the same time, the models differentiate between pollution plumes and natural phenomena like clouds and smoke from wildfires. The named U-Net architecture serves to segment emissions regions automatically. Supervised training of the model adopts cross-entropy loss, while regularized techniques maintain their resistance to overfitting.

I am running a few minutes late; my previous meeting is over.

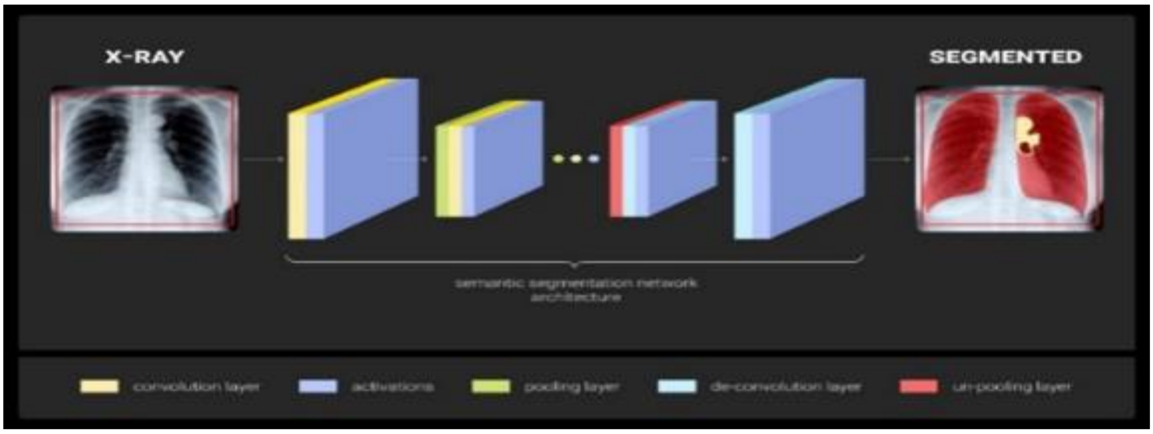

Figure 3 CNN-based semantic segmentation

4.2.2. Integrated Spectral-Spatial Analysis and Geo-Temporal Fusion

The detection of greenhouse gases relies on analysis that combines multiple spatial and spectral data streams. Since these regions showcase the most distinct absorption characteristics, detecting methane CH4 and carbon dioxide CO2 gases occurs by analyzing Hyperspectral and multispectral imagery within SWIR and TIR bands.Spatial masks from CNN outputs are applied to spectral features produced in specific bands. Using visual patterns together with spectral evidence reduces the level of ambiguity and provides stronger detection capabilities. The system unifies spatial patterns, temporal dynamics, and spectral signatures with a single framework to track both locations and emission phenomena' time-evolution patterns. Such an integrated method increases detection reliability by reducing false results across various operational conditions.

4.3. Emissions estimation model

4.3.1. Confidence-Weighted Emissions Estimation with Uncertainty Bounds

A parallel analysis process on Hyperspectral and multispectral imagery uses spectral methods to detect specific absorption patterns of greenhouse gases. The technique analyzes specific bands from shortwave infrared (SWIR) along with thermal infrared (TIR) bands, where pronounced absorption signatures of CH_4 and CO_2 gases are present. Spectral features are matched with spatial masks originating from CNN outputs, integrating visual and spectral evidence. This combined approach reduces uncertainty and enhances detection assurance.

Each emissions estimate is reported with statistical uncertainty bounds (± values) and calculated using bootstrapped ensemble methods. In addition, model performance metrics such as the F1 Score (evaluating the trade-off between false positives and false negatives) are included alongside emission predictions to indicate detection reliability. To support ESG reporting needs, the carbon cost of model training and inference (in kg CO_2-equivalent) is calculated and disclosed for transparency regarding the system's environmental impact.

Table 4 Example of confidence-weighted emissions estimation output

Location	Predicted CO_2 (tons/day)	95% Confidence Interval (tons/day)	Confidence Score	Ground Sensor Validation	Final Estimate (tons/day)	F1 Score	Model Carbon Cost (kg CO_2e)
Plant A	5,200	5,050–5,350	0.92	Confirmed	5,050	0.91	150
Plant B	3,800	3,400–4,200	0.65	Not available	3,300	0.78	140
Transit Hub C	1,200	1,140–1,260	0.88	Confirmed	1,180	0.89	120

4.3.2. Auditable Data Streams for ESG and Compliance

The system preserves a comprehensive emissions audit trail, recording each data point with timestamp, location, data sources, and model reliability assessments, including statistical uncertainty bounds. A standardized metadata protocol ensures emissions records are transparent, interoperable, and easily verifiable by ESG auditors and regulatory agencies. Data integrity is fortified by a tamper-resistant blockchain platform and cryptographic hashing, ensuring decentralized storage and immutability. Disclosure of the model's carbon cost further enhances system accountability by quantifying the emissions footprint associated with emissions monitoring.

5. Case Studies / Application Scenarios

5.1. Industrial sector applications

AI-powered systems for car emissions monitoring provide industry programmers with operational value, demonstrating such technologies' ability to ensure environmental accountability by using data. The highest potential for carbon emissions tracking lies in the energy generation sector, manufacturing, and transportation, which generate the most significant emissions.

5.1.1. PlantsPower

The operation of power plants using fossil fuels serves as a primary facilities that discharge the greenhouse gases CO_2 and other GHG emissions. This system employs data from Sentinel-5p remote sensing satellites and Landsat and VIIRS (Visible Infrared Imaging Radiometer Suite) high-resolution imagery to analyze CO_2 plume spectral signatures, enabling them to detect emissions in their source locations. Attachment capabilities allow for precision emission event localization. The satellite detection process becomes more accurate because real-time comparison between ground-based CO_2 and NOx readings verifies results. A geo-temporal learning model system analyses extensive temporal emission patterns as part of its operational framework and seasonal power generation changes.

5.1.2. Manufacturing Units

Multiple emission sources withinmanufacturing facilities are difficult because their diverse operating processes create such circumstances. Industries' cement making, metal refining, and chemical synthesis processes produce varying gas emissions, consisting of CO_2, CH_4, SO_2, and volatile organic compounds (VOCS). Deep-learning industrial models adapted for factory operations demand that the system process data through multiple spectral analyses.Furthermore,discovering geo-located emission clusters requires data from satellite passes and drone imagery since satellite resolution remains low in dense industrial zones. Using recurring satellite data and high-frequency drone footage enables creatingexact heat maps that expose emission release points.

Table 5 Emission detection accuracy by sector and sensor type

Sector	Sensor Type	Detection Accuracy (%)	False Positive Rate (%)
Power Plants	Satellite + Ground Sensors	94.5	3.1
Cement Manufacturing	Satellite + Drone Imagery	90.8	4.2
Oil Refineries	Multi-modal Fusion	92.3	3.7

5.1.3. Transportation hubs

Continuous vessel and power system operations at ports and airports create emissions that function as pollutants. The system examines transport patterns before linking them to published emission information about various transportation techniques. The detection of aircraft landing operations hotspots and diesel truck hotspots from stationary port locations is executed via airborne sensors by operators.Satellite thermal data processed by machine learning algorithms require local meteorological adjustments to determine emission quantities and their time durations. The system maintains high precision in detecting transport emissions by effectively linking traffic data from multiple sources to its emissions monitoring features.

5.2. Evaluation metrics

A set of comprehensive metrics evaluates the system's performance and robustness across diverse industrial contexts. These metrics span technical accuracy, operational reliability, and deployment scalability.

5.2.1. Accuracy and Precision

The system identifies emission events correctly among all detected activities with precision as its measurement metric. The exactness of detection systems becomes essential within densely populated industrial regions to avoid unnecessary alarm reports.

5.2.2. False Positive and Negative Rates

The ability of regulatory reliability depends heavily on both correct and incorrect emission detection and missed actual emissions identification. The confidence-weighted estimation model verifies data streams to satisfy the verification criteria that ESG auditors demand.

5.2.3. Latency and Real-Time Responsiveness

The system minimizes data processing latencies by using edge computing, particularly applicable to drone and ground sensor information. Near real-time performance depends on the sensor source because it benchmarks operations from minutes to seconds.

5.2.4. Scalability across geographic and industrial domains

The system employs a cloud-native modular architecture in different geographical locations, spanning urban areas to distant industrial districts. It is evaluated by processing additional satellite data and sensors to find performance maintenance levels.

Table 6 System evaluation metrics summary

Metric	Description	Benchmark Value
Detection Accuracy	% of correct emission identifications	≥ 90%
False Positive Rate	Incorrect alerts per detection	≤ 5%
Processing Latency	Time to generate alert (avg.)	< 5 minutes
Geographic Scalability	Number of supported monitoring zones	> 100 regions

5.3. Pilot studies and simulated scenarios

The system was tested in a simulated pilot project of Eastern European power plants, utilizing Sentinel-5p historical satellite data and sensor data acquired through IoT nodes in real-time. The monitoring system detected 212 emission occurrences during 30 days and earned validation for 198 events from independent ground truth records, which produced a verification accuracy of 93.4%. The system could differentiate operational irregularities from scheduled maintenance by adding spatial and temporal variables. The analysis at Port of Los Angeles used drone-based thermal scanners and satellite information to combine detection of ship exhaust emissions with harbor delivery processes. During the test, the system showcased how it tracks emissions in active shipping zones while automatically adapting its operations to accommodate vessel movement dynamics because of its volatile environment learning capability.

6. Discussion

6.1. Implications for policy enforcement

The automated carbon emissions monitoring system can create essential changes in environmental policy enforcement conducted by governments and regulatory bodies. Standard monitoring systems depend on information that industries supply and irregular manual site examinations, yet these methods frequently lead to inconsistent results, delayed reporting, and biased reports. AI-powered computer vision systems working with satellite remote sensing technologies enable automatic emission detection and accurate quantification during real-time monitoring without depending on industrial self-reporting data. Instant and objective regulatory control through this system enhances compliance monitoring while creating substantial regulatory oversight. The proposed system produces time-stamped data streams with geographic locations that help ESG auditors and law enforcement agencies verify operations. Such verifiable data sets enable environmental regulators to establish dynamic caps linked to penalties and compliance standards for international accords such as the Paris Climate Accord.

6.2. Potential to transform global emissions tracking

Standardized remote emissions monitoring throughout national borders becomes possible through this technology because it serves essential needs for worldwide climate governance. The Global South and numerous other regions struggle to monitor continuous emissions because they lack infrastructure and technical monitoring capabilities. AI systems with satellite data functions can handle structural barriers to obtain environmental data through scalable and fair distribution methods.Electronic systems help organizations develop and adjust their policymaking strategies. Policy models can achieve dynamic regulatory responses through real-time emissions data collected from different regions, allowing adaptive environmental defenses to be developed. The approach enables national and international levels to achieve better governance through enhanced speed and informed decision-making processes.

6.3. Advantages over traditional methods

Compared to conventional emissions monitoring techniques, the integration of computer vision and remote sensing offers a set of distinct advantages:

Table 6 Comparison of traditional environmental monitoring methods

Feature	Traditional Methods	AI-Powered Monitoring
Temporal Resolution	Intermittent sampling, often delayed	Near real-time data collection and analysis
Spatial Resolution	Localized, dependent on ground sensors	Wide-area coverage via satellite imagery
Scalability	Limited by physical infrastructure	Highly scalable with cloud-based processing
Cost Efficiency	High operational and maintenance costs	Reduced cost after deployment
Objectivity	Prone to self-reporting bias	Data-driven, independent of industrial reporting

Combining satellite data and ground sensors provides wide-ranging overview capabilities and detailed spatial precision. Combining convolutional neural networks with training data about emission spectral and spatial patterns allows specific emission detection accuracy through geo-temporal fusion mechanisms. The confidence-weighted estimation model develops reliability by assigning certainty levels to detected emissions,reducing false positive errors, and enabling data traceability.

6.4. Limitations and future directions

The present strategy faces multiple obstacles despite its capability to bring transformation. The main obstacle regarding satellite-derived data accuracy emerges from changing atmospheric conditions. The reliability of spectral readings becomes unreliable when satellite passes encounter cloud cover and aerosols, in addition to periods of missing data. Some limitations of data fusion systems can be reduced by incorporating ground-based sensors, but their geographical spread affects data availability. The real-time processing operations are constrained by their high computational complexity. Whole-scale satellite information processing and deep learning algorithms require powerful computing facilities and extensive data storage elements. The benefits of cloud-based solutions are offset by costs associated with operation and data privacy standards that become challenging as different borders are involved.

The research field needs to enhance the stability of CNN models, which face challenges due to environ/mental conditions such as seasonality and cloud obstructions. Transfer learning and domain adaptation techniques implemented into the system would boost its capacity to understand different industrial sites and locations worldwide. The system performance can be expanded through new emerging technologies, including IoT-enabled environmental sensors, UAVS, and edge computing capabilities. The system requires scalable infrastructure design. Developing worldwide data analysis platforms alongside policy tools will allow developing nations to perform transparent emissions reporting. Developing open-source frameworks and international data-sharing agreements will speed up worldwide assistance in climate governance.

7. Conclusion

The system described here utilizes three different technological approaches that integrate artificial intelligence vision algorithms with spectral analysis to conduct automatic carbon emissions detection at scale. The system uses spatiotemporal animations of CNNS together with satellite imagery (Sentinel-5p along with Landsat) and environmental sensors to conduct immediate detection and quantify emissions released by primary industrial sources. The confidence-weighted emissions estimation model introduces data reliability features that overcome three main weaknesses of present methods, stemming from data reporting delays and insufficient coverage and manual processes. The proposed monitoring system creates substantial progress for environmental detection through its approach, which provides transparent verification at reasonable costs while covering multiple regional and industrial sectors. The system demonstrates widespread usage capabilities, enabling organizations to fulfill requirements from domestic environmental laws and international climate goals through Paris Agreement alignment. The universal tracking method can boost policy management effectiveness and increase ESG transparency to deliver substantial support for global carbon reduction targets.

Future innovations should consider validating the methodology in real-world settings, creating models that generalize across multiple geographic areas, and integrating the system with IoT-based and UAV-based technologies. To achieve ultimate success, deploying this system requires joint efforts from researchers specializing in AI and climate science, engineers working on satellites, and those involved in policy creation to guarantee ethical governance, practical effectiveness, and technical stability. Climate change demands immediate action to develop broad and intelligent monitoring solutions because of its rapid pace of progression. According to the groundwork from this research, such systems require collaborative efforts to advance development and implementation at a large scale.

References

[1] Liu, J., & Zhang, Z. (2023). Integrated energy carbon emission monitoring and digital management system for smart cities. Frontiers in Energy Research, 11. https://doi.org/10.3389/fenrg.2023.1221345

[2] Zhou, C., Lin, X., Wang, R., & Song, B. (2023). Real-Time Carbon Emissions Monitoring of High-Energy-Consumption Enterprises in Guangxi Based on Electricity Big Data. Energies, 16(13). https://doi.org/10.3390/en16135124

[3] Liu, G., Chen, R., Xu, P., Fu, Y., Mao, C., & Hong, J. (2020). Real-time carbon emission monitoring in prefabricated construction. Automation in Construction, 110. https://doi.org/10.1016/j.autcon.2019.102945

[4] Yang, W., Yi, G., Zhiyu, Z., Yue, C., Wang, X., Shuai, L., … Dawei, Y. (2024). Correlation Analysis and Monitoring Method of Carbon Emissions in the Steel Industry Based on Big Data. Strategic Planning for Energy and the Environment, 43(1), 27–54. https://doi.org/10.13052/spee1048-5236.4312

[5] Zhou, S., Zhang, X., Chu, S., Zhang, T., & Wang, J. (2023). Research on remote sensing image carbon emission monitoring based on deep learning. Signal Processing, 207. https://doi.org/10.1016/j.sigpro.2023.108943

[6] Pithon, S., Jubelin, G., Guitet, S., & Gond, V. (2013). A statistical method for detecting logging-related canopy gaps using high-resolution optical remote sensing. International Journal of Remote Sensing, 34(2), 700–711. https://doi.org/10.1080/01431161.2012.70679

[7] Huang, M., & Asner, G. P. (2010). Long-term carbon loss and recovery following selective logging in Amazon forests. Global Biogeochemical Cycles, 24(3). https://doi.org/10.1029/2009GB003727

[8] Yi, L. I. U., Jing, W. A. N. G., Ke, C. H. E., Zhaonan, C. A. I., Dongxu, Y. A. N. G., & Lin, W. U. (2021). Satellite remote sensing of greenhouse gases: Progress and trends. National Remote Sensing Bulletin, 25(1), 53-64. https://dx.doi.org/10.11834/jrs.20210081

[9] Chen, Y., Guerschman, J. P., Cheng, Z., & Guo, L. (2019). Remote sensing for vegetation monitoring in carbon capture storage regions: A review. Applied energy, 240, 312-326. https://doi.org/10.1016/j.apenergy.2019.02.027

[10] Hu, K., Feng, X., Zhang, Q., Shao, P., Liu, Z., Xu, Y., ... & Xia, M. (2024). Review of satellite remote sensing of carbon dioxide inversion and assimilation. Remote Sensing, 16(18), 3394. https://doi.org/10.3390/rs16183394

[11] Gaur, L., Afaq, A., Arora, G. K., & Khan, N. (2023). Artificial intelligence for carbon emissions using systems of systems theory. Ecological Informatics, 76, 102165. https://doi.org/10.1016/j.ecoinf.2023.102165

[12] Delanoë, P., Tchuente, D., & Colin, G. (2023). Method and evaluations of the effective gain of artificial intelligence models for reducing CO2 emissions. Journal of Environmental Management, 331, 117261. https://doi.org/10.1016/j.jenvman.2023.117261

[13] Dong, M., Wang, G., & Han, X. (2024). Impacts of artificial intelligence on carbon emissions in China: in terms of artificial intelligence type and regional differences. Sustainable Cities and Society, 113, 105682. https://doi.org/10.1016/j.scs.2024.105682

[14] Tseng, C. J., & Lin, S. Y. (2024). Role of artificial intelligence in carbon cost reduction of firms. Journal of Cleaner Production, 447, 141413. https://doi.org/10.1016/j.jclepro.2024.141413

[15] Arya, A., Bachheti, A., Bachheti, R. K., Singh, M., & Chandel, A. K. (2024). Role of Artificial Intelligence in Minimizing Carbon Footprint: A Systematic Review of Recent Insights. Biorefinery and Industry 4.0: Empowering Sustainability, 365-386. https://doi.org/10.1007/978-3-031-51601-6_14

[16] Illarionova, S., Shadrin, D., Tregubova, P., Ignatiev, V., Efimov, A., Oseledets, I., &Burnaev, E. (2022). A survey of computer vision techniques for forest characterization and carbon monitoring tasks. Remote Sensing, 14(22), 5861. https://doi.org/10.3390/rs14225861

[17] Nagy, M., &Lăzăroiu, G. (2022). Computer vision algorithms, remote sensing data fusion techniques, and mapping and navigation tools in the Industry 4.0-based Slovak automotive sector. Mathematics, 10(19), 3543. https://doi.org/10.3390/math10193543

[18] Huang, C., Xie, L., Chen, W., Lin, Y., Wu, Y., Li, P., ... & Deng, J. (2024). Remote-sensing extraction and carbon emission reduction benefit assessment for centralized photovoltaic plants in Agrivoltaic systems. Applied Energy, 370, 123585. https://doi.org/10.1016/j.apenergy.2024.123585

[19] Liu, G., Chen, R., Xu, P., Fu, Y., Mao, C., & Hong, J. (2020). Real-time carbon emission monitoring in prefabricated construction. Automation in Construction, 110, 102945. https://doi.org/10.1016/j.rse.2013.04.005

[20] Lin, S., Zhang, C., Ding, L., Zhang, J., Liu, X., Chen, G., ... & Chai, J. (2022). Accurate recognition of building rooftops and long-term carbon emission reduction assessment from rooftop solar photovoltaic systems fusing GF-2 and multi-source data. Remote Sensing, 14(13), 3144. https://doi.org/10.3390/rs14133144

[21] Himeur, Y., Rimal, B., Tiwary, A., & Amira, A. (2022). Using artificial intelligence and data fusion for environmental monitoring: A review and future perspectives. Information Fusion, 86, 44-75. https://doi.org/10.1016/j.inffus.2022.06.003

[22] Ounoughi, C., & Yahia, S. B. (2023). Data fusion for ITS: A systematic literature review. Information Fusion, 89, 267-291. https://doi.org/10.1016/j.inffus.2022.08.016

[23] Okafor, N. U., Alghorani, Y., & Delaney, D. T. (2020). Improving the data quality of low-cost IoT sensors in environmental monitoring networks using data fusion and machine learning. ICT Express, 6(3), 220-228. https://doi.org/10.1016/j.icte.2020.06.004

[24] Chang, N. B., & Bai, K. (2018). Multisensory data fusion and machine learning for environmental remote sensing. CRC Press. https://doi.org/10.1201/9781315154602

[25] Di Curzio, D., Castrignanò, A., Fountas, S., Romić, M., &Rossel, R. A. V. (2021). Multi-source data fusion of big spatial-temporal data in soil, geo-engineering, and environmental studies. Science of the Total Environment, 788, 147842. https://doi.org/10.1016/j.scitotenv.2021.147842